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Using Knowledge Graphs and Human-Centric Artificial Intelligence for Reconfigurable Supply Chains: A Research Framework

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Abstract: Reconfigurable supply chains received increasing interest from academia and industry in the past years, especially because recent events such as the COVID-19 pandemic revealed the vulnerability of present supply chains. Especially the rapid digitalization and the emergence of artificial intelligence in supply chain management create new opportunities for implementing reconfigurable supply chains. In this paper, we propose a concept that uses a knowledge graph and graph-based artificial intelligence to recommend reconfigurations of the supply chain. Due to the importance of these strategic decisions, the concept considers a human-centric approach using a recommender system. The knowledge graph exploits the inherent graph structure of supply chains to create a machine-readable and human-understandable database that also supports reasoning. Finally, we provide three research hypotheses and examine the integration of open-source knowledge graphs and news monitoring tools.

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Keywords: Reconfigurable supply chains; Knowledge graphs; Supply chain management; Human-centric artificial intelligence; Graph neural networks; Open data

1. INTRODUCTION

Supply chain configuration and operation are highly relevant for corporate success and have been topics of interest for many years in academia and industry. Many supply chains became highly optimized structures focusing on efficiency and profit because companies took globalization, low tariffs, and stable trading rules for granted. However, in the last years the global situation became increasingly unstable, and several recent events revealed the vulnerability of global supply chains. Especially the temporary closures of factories in different regions around the world caused by the COVID-19 pandemic affected supply chains. In combination with other events such as the trade war between the USA and China, the withdrawal of the UK from the European Union or the temporary Suez Canal obstruction, the disruptions became a serious threat that lead to shortages of different products. Stricter entry regulations resulted in longer and unpredictable lead times and broke long-distance supply chains with low inventories. Currently, the situation does not seem to be improving soon, also due to more frequent extreme weather events and new outbreaks of infectious diseases caused by the

climate change (Javorcik, 2020; Schroeder et al., 2021). As a result of these trends, many companies started to rethink their supply chain configuration and shift from a pure focus on efficiency and profit to a more resilient operation (Javorcik, 2020). A reaction to the COVID-19 pandemic would have required to quickly retake strategic decisions such as supply chain design and supplier selection that usually have a planning horizon of 2-5 years. Current supply chains were simply not designed for that. The concept of reconfigurable supply chains that focus on the adaption to changing circumstances by dynamically adding, removing, or replacing units in the supply chain offers a possible solution to decrease the reaction time (Dolgui et al., 2020). A recent survey by Schroeder et al. (2021) showed that only 20% of shipping companies and logistics service providers had a comprehensive risk management before the pandemic but the procurement of 64% was negatively affected by the pandemic. Furthermore, 70% of the companies plan to invest in business analytics, artificial intelligence (AI), and the digitalization of business processes after the pandemic which creates an urgent need for further research on how to improve risk management and decision-making in supply chains.

However, literature on reconfigurable supply chains is still limited to highly conceptual considerations that all agree that business analytics and AI are important enablers (Chandra and Grabis, 2016; Dolgui et al., 2020; Kelepouris et al., 2006). Therefore, we identify research gaps and propose a research framework for enabling reconfigurable supply chains with human-centric AI in this paper. Section 2 summarizes the existing literature on reconfigurable supply chains and reconfigurable manufacturing systems. Section 3 presents the state-of-the-art on knowledge graphs in supply chain management because knowledge graphs are an important basis for the research framework that is presented in section 4 and section 5. Finally, we draw conclusions on future research in section 6.

2. RECONFIGURABLE SUPPLY CHAINS

To present the current state-of-the-art for reconfigurable supply chains it is important to give a short overview on reconfigurable manufacturing systems first. Reconfigurable manufacturing systems were first proposed by Koren et al. (1999) as a reaction to unpredictable market changes that occurred with increasing pace in the late 1990s. These challenges include for example decreasing product life cycles, fluctuations in demand and product mix, new government regulations regarding safety and environment, and fast changing process technology. The basic idea of reconfigurable manufacturing systems is combining the high throughput of dedicated production lines and the flexibility of flexible manufacturing systems to build a superior system that can react rapidly and cost-effectively to changes. Other major drivers for introducing reconfigurable manufacturing systems were the rising globalization and the increasingly global competition which require a more responsive manufacturing system. Bortolini et al. (2018) identified five main research streams in a recent literature review. The literature review showed that applied research and field application constitute the most important research stream which highlights the relevance not only for academia but especially for industry. In addition, current trends such as Industry 4.0 and cyber-physical systems contributed to the dissemination of reconfigurable manufacturing systems, and their key technologies enabled the implementation in industrial environments (Qin et al., 2016). Since the initial publication, the market challenges have even intensified further (Koren et al., 2018). The ongoing intensification of market challenges steadily shifts the scope of reconfigurability from manufacturing systems to entire supply chains which also caused the development of a framework for reconfigurable supply chains. However, a distinction must be made between reconfigurable supply chains and classic supply chain reconfiguration. Classic supply chain reconfiguration has been a topic of interest since the late 1990s, but it was usually considered as a one-time adaption of existing supply chains to new circumstances. On the contrary, reconfigurable supply chains focus on the dynamic adaption to changing circumstances. The concept received decent attention in the last few years but does not have a lot of contributions yet. Reconfigurable supply chains were first proposed by Kelepouris et al. (2006). Later, Chandra and Grabis (2016) as well as Dolgui et al. (2020) published the most recognized and comprehensive frameworks. Kelepouris et al. (2006) define reconfigurable supply chains as networks that are

“designed for easy rearrangement or change of supply network entities in a timely and cost-effective manner”. The rearrangement of supply chain entities incorporates the long-term decisions network design, supplier selection and product program which usually have a long planning horizon, involve high costs and significantly impact the supply chain performance. Reconfigurable supply chains describe the target concept where reconfigurations happen dynamically as a consequence of certain events within a short planning horizon (Chandra and Grabis, 2016; Zidi et al., 2021a). Reconfigurability has six characteristics that apply to reconfigurable manufacturing systems as well as reconfigurable supply chains (Biswas et al., 2019; Kelepouris et al., 2006; Koren et al., 1999; Zidi et al., 2021a):

- (1) Modularity enables the clustering into independent modules.
- (2) Integrability enables the introduction of new resources, products, and processes.
- (3) Convertibility enables the changeover between existing products.
- (4) Diagnoseability enables the identification of problems in the supply chain.
- (5) Scalability enables the change of capacity.
- (6) Customization enables the fast adaption within a product family.

Reconfigurability has the potential to increase the robustness, flexibility, and agility of supply chains. The dynamic reconfiguration makes supply chains more robust to withstand disruptions such as natural disasters, labour disputes or delivery problems. Not only disruptions can cause reconfigurations but also delivery terms such as cheaper prices, higher quality or shorter delivery times which leads to a general flexibility and agility. However, reconfigurability also raises new challenges. It further complicates supply chain management by introducing a new decision-making domain. Moreover, the fast change of suppliers hampers supply chain collaboration and reduces the trust, impairs information sharing and requires a high level of technology in the manufacturing system for processing parts from multiple suppliers (Chandra and Grabis, 2016). Dolgui et al. (2020) consider reconfigurability as the central factor for achieving a digital, resilient, sustainable, and efficient supply chain and highlight the relationships between these requirements in a framework called X-Network. The framework comprises a matrix with three levels and four design principles that specifies the respective enabling technologies. Furthermore, they introduce two new principles which are supply chain meta-structures and dynamic autonomous services. According to them, a dynamic meta-structure is an integrity of the organizational, product, process-functional, information and financial structure of a supply chain. A dynamic autonomous service is a composition of supply chain units within the meta-structure. For example, a supply chain unit, respectively an enterprise, can change its role in the process-functional structure and shift from supplier to manufacturer. Chandra and Grabis (2016) mention the three main aspects decision-making, physical implementation, and logical implementation that must be considered when implementing reconfigurable supply chains. Decision-making determines when and how to reconfigure supply chains. The physical implementation comprises all structural requirements regarding facilities

and products that are necessary to enable reconfigurable supply chains. The logical implementation considers the design of business processes and information systems. Recent technologies such as software, sensors and communication technologies can already meet the technological requirements for reconfigurable supply chains. For instance, Cândido et al. (2009) propose a service-oriented architecture for industrial automation at the shopfloor level. Decision-making and logical implementation received less attention. Instead, most contributions present theoretical frameworks (Chandra and Grabis, 2016; Dolgui et al., 2020; Kelepouris et al., 2006) or address special issues such as modularity metrics (Zidi et al., 2021b), reconfigurability metrics (Biswas et al., 2019) or performance evaluation (Zidi et al., 2021c).

3. KNOWLEDGE GRAPHS IN SUPPLY CHAIN MANAGEMENT

A knowledge graph is a simple but powerful data model whose basic units are entities with attributes and relations. They became popular in 2012 when Google complemented its web search engine with knowledge graphs (Singhal, 2012). The terms knowledge graph and ontology have often been used as synonyms, but according to the definition review of Ehrlinger and Wöß (2016), a knowledge graph is superior and more complex because it also includes a reasoning engine and integrates multiple data sources. Reasoning engines for knowledge graphs are often based on AI, for instance graph neural networks that are a new class of machine learning algorithms for handling graph structures as inputs (Arora, 2020). The promotion of knowledge graphs was mainly driven by the semantic web community as an effort to make the internet machine-readable Ehrlinger and Wöß (2016). However, three main characteristics make knowledge graphs also interesting for application in enterprises (Gomez-Perez et al., 2017; Zou, 2020):

- (1) Knowledge graphs are machine-readable.
- (2) Knowledge graphs are understandable for humans.
- (3) Knowledge graphs extend information with context and enable reasoning.

Knowledge graphs have been successfully applied in several domains such as healthcare, cybersecurity, finance and education (Zou, 2020). However, in supply chain management, the application of knowledge graphs is still rare, although supply chains face similar challenges as the other domains: Increasingly available structured and unstructured data from different sources, rapid digitalization and the emergence of AI (Schniederjans et al., 2020). Currently, many companies store their data in multiple isolated data silos which indeed works for decision-making in delimited domains. However, connecting all these data has the potential to boost the performance of data analytics and AI in supply chains (Schroeder et al., 2021; Song et al., 2017). Knowledge graphs are a promising tool to create a consistent database for analytics.

Especially the natural graph structure of supply chains makes it suitable for the representation in form of graphs. The few existing publications on knowledge graphs in supply chain management mainly focus on risk-related topics and resilience and all of them were published in the last

few years. For instance, Zhang et al. (2019) implemented a knowledge graph for supply chain credit risk assessment to evaluate the risk of bankruptcy of suppliers. Ramzy et al. (2021) propose a dynamic pricing model for semiconductor supply chains based on a knowledge graph. Another use case is the application of link prediction algorithms that have their origin in biological networks and social network analytics (Lü and Zhou, 2011). Link prediction has the objective to reveal hidden connections in large supply networks that are unknown from the point of view of a single company. By this, companies can increase their knowledge on unknown lower-tier or higher-tier suppliers. Brintrup et al. (2018) use naïve Bayes and logistic regression to estimate the likelihood that two suppliers interact with each other based on the supply network structure. Aziz et al. (2021) and Kosasih and Brintrup (2021) use graph neural networks for the same task and achieve an accuracy of more than 85%. These three approaches are promising examples of the deployment of knowledge graphs in supply chain management. Ontologies are more widespread in supply chain research, but their purpose is slightly different from knowledge graphs. They are usually used for modelling supply chain processes and information systems in a rather abstract manner. For instance, Ameri and Kulvatunyou (2019) develop a supply chain reference ontology to make supply chains interoperable and improve collaboration. Geerts and O’Leary (2014) describe their ontology as a supply chain of things that has the objective to gather information on the location of objects along the supply chain. Grubic and Fan (2010) present a literature review on supply chain ontologies.

4. RESEARCH NEED AND RESEARCH FRAMEWORK

As the reasoning engines of knowledge graphs are designed to adjust the edges and weights, use cases in supply chain management where the relations are dynamic are most interesting. So far, there were only very few approaches that exploit this characteristic because supply chains were considered to be static. The only exception are the supply chain visibility concepts of Brintrup et al. (2018), Aziz et al. (2021) and Kosasih and Brintrup (2021). Reconfigurable supply chains reveal a completely new use case for knowledge graphs because the weights can be used to model the dynamics of reconfigurations. For instance, the weighted arcs can represent the probabilities of establishing the respective supply relation. Regarding the previous sections, we can identify two major research needs to be addressed:

- (1) **A quantitative proof of concept for reconfigurable supply chains:** Authors agree that reconfigurable supply chains can potentially increase the resilience, flexibility, and agility of supply chains but there is no proof of concept. Furthermore, no benchmark problems or industrial case studies exist which evaluate the performance of reconfigurable supply chains in a quantitative way. However, companies are ready to invest in technologies that increase the resilience (Schroeder et al., 2021).
- (2) **AI solutions for supply chain management based on knowledge graphs:** Although characteristics of knowledge graphs are promising to handle big

data in supply chain management, no case studies exist that investigate the suitability of knowledge graphs as a basis for AI algorithms in supply chain management.

We think that a quantitative proof of concept for reconfigurable supply chains with a focus on knowledge management and human-centric AI should be of great interest. Specifically, three research hypotheses must be evaluated.

Hypothesis 1. Reconfigurability can increase the performance of supply chains, especially the resilience, flexibility, and agility.

A quantitative proof of concept must be developed to evaluate the resilience, flexibility, and agility of reconfigurable supply chains. As these performance indicators are difficult to measure quantitatively and there are no benchmark problems, the first step is to specify a framework for benchmark problems concerning reconfiguration decisions.

Hypothesis 2. Knowledge graphs are an ideal basis for data integration, decision support systems and AI deployment in supply chains.

Supply chains are characterized by multiple independent units with incompatible and isolated information systems and several data sources (Kache and Seuring, 2017; Zhang et al., 2019). Knowledge graphs can potentially support data integration and consequently the implementation of decision support systems and AI in supply chains. Compared to traditional relational databases, knowledge graphs provide not only isolated and static data but also context and logic. The presence of dynamic contextual information enables reasoning because the arrangement of data in knowledge graphs is reminiscent to the human brain. It has the significant advantage that it is machine-readable, human-understandable and allows structured queries at the same time. The dissemination of knowledge graphs for large-scale applications in big tech companies also indicates that knowledge graphs could be promising tools for information management in supply chains, especially because supply chains have a natural graph structure.

Hypothesis 3. Graph-based AI has a higher solution quality and trustworthiness for strategic and tactical decision-making in supply chain management than traditional black-box AI.

As reconfiguration decisions are strategic decisions, the risk of using traditional black-box AI is too high because trustworthiness is more important for strategic and tactical decisions than decision-making time. Graph-based AI algorithms have high synergies with knowledge graphs and the natural graph structure of supply chains.

5. CONCEPTUAL AI SYSTEM

The concept considers supply chains as directed graphs with nodes and arcs like in graph theory (See Figure 1). Each node represents a facility in the supply chain, e. g. plants, warehouses, or customers, whereas each arc represents a directed connection between two nodes, e. g. material flow and/or information flow. Each reconfiguration changes the graph structure by using one or more of the following operations:

- Adding, removing, and replacing nodes
- Adding and removing arcs
- Reversing the arc direction

The AI system features a supply chain knowledge graph that has two functions. On the one hand, it directly represents the structure of the supply network (blue nodes and arcs in Figure 1). The weights on the arcs represent the probabilities of establishing the respective supply relation between two nodes. If the probability exceeds a certain threshold (0.5 in Figure 1) the AI recommends establishing the connection. On the other hand, the supply chain knowledge graph includes additional information (grey nodes and arcs in Figure 1) that is related to the current state of the supply network, e. g. ongoing shipments, disruptions, or master data. The grey nodes are the basis for the graph-based AI to compute the probabilities of the arcs. Basically, the knowledge graph is a digital representation of the supply network that enriches it with additional information. It is similar to the concept of the digital twin which is a digital representation of a physical object that exchanges data in both directions (Kritzinger et al., 2018). The graph-based AI continuously gathers information from the knowledge graph and dynamically adjusts the weights, respectively reconfigures the system. However, there are two differences to traditional digital twins: Supply chains are no physical objects with physical controls and reconfigurations require approval of a human operator. Due to the importance of such decisions, the concept works like a recommender system that also includes the human in the loop. Whenever major changes occur in the network, the graph AI recommends reconfigurations to the human that he can choose from. The possible reconfigurations are ranked according to their weights and include reasoning. The human can then choose his preferred option and the graph-based AI receives feedback.

6. CONCLUSION

The COVID-19 pandemic has exposed the vulnerability of modern supply chains and the need of fast and efficient reactions in case of disruptions. Reconfigurability in supply chains, which evolved from the concept of reconfigurable manufacturing systems, pursues the objective of reducing the time for strategic and tactical decisions, by introducing dynamic reconfigurable services that allow a quick change of supply relations. Although this concept is very promising, reconfigurable supply chains are still far from being implemented in reality. Furthermore, literature is limited to highly conceptual considerations that nevertheless received a lot of attention. These concepts all agree that AI algorithms are enablers for reconfigurable supply chains. In this paper, we have highlighted the lack of precise concepts for applying AI in reconfigurable supply chains, and the need of benchmark problems of reconfigurable supply chains on which the feasibility of AI methods can be evaluated. To close both gaps, we have proposed a human-centric AI approach based on a knowledge graph that integrates the data of all participants in the supply chain. As knowledge graphs can use the problem structure of reconfigurable supply chains, they are useful as the backbone for the dynamic reconfiguration problem on which more complex AI applications can be built. The optimization algorithm gathers information from the

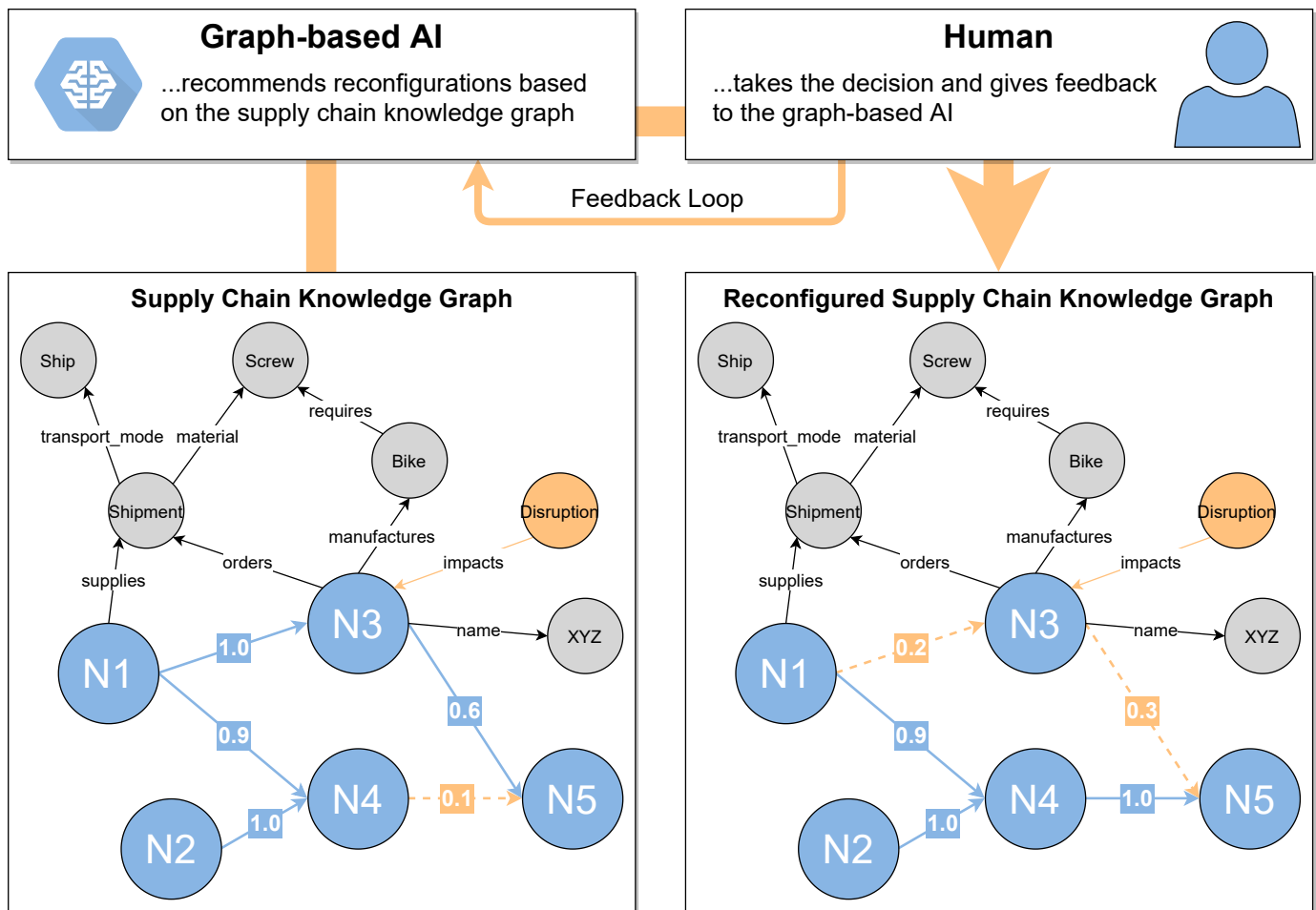


Fig. 1. Reconfiguration process. A disruption impacts node 3 (N3) and triggers a potential reconfiguration. The graph-based AI recalculates the probabilities for each supply relation. In this case, the algorithm recommends deactivating the relations N1-N3 as well as N3-N5 and activate the relation N4-N5 instead. The human confirms the decision and returns feedback to the AI algorithm.

knowledge graph and dynamically reconfigures the system based on the inputs. It also utilizes the graph structure of the reconfiguration problem by interpreting the nodes and arcs as a trainable network whose weights can be adjusted by backpropagation. Despite the commonly used graph representation of supply chain problems, there are only very few applications that use the inherent structure of the supply chain or knowledge graphs. To enrich the supply chain knowledge graph with contextual information, the integration of open-source knowledge graphs such as Wikidata or DBpedia is very promising. For example, DBpedia, which is a crowd-sourced community project, uses data from Wikipedia and currently comprises approximately 228 million entities (Lehmann et al., 2015). Another interesting extension is the implementation of real-time disruption monitoring with open databases. For example, the GDELT project provides a global open-source database of events gathered from broadcast, print and web news (Leetaru and Schrodtt, 2013). Online newspapers report the causes for supply chain disruptions, for instance natural disasters or strikes, usually very quickly. Therefore, these data sources can significantly enhance the data availability for the AI system and potentially improve the reconfiguration decision-making. However, an integration of real-world data is only useful for real-world supply

chain problems but has limited usefulness for benchmark problems.

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